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SOME EXPERIMENTS IN POINT PATTERN MATCHING

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ABSTRACT

Given two pictures of a scene taken by different sensors or at different times, one way of matching the two pictures is to extract a set of distinctive local features from each, and then match the resulting point patterns. This paper investigates the sensitivity of point pattern matching to various types of noise and distortion, including omissions and additions, random walks, rotation and rescaling, as well as the use of different feature detection operators to extract the points. The effects of additional information (e.g., feature types) in overcoming the effects of noise is also studied.

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1. Introduction

Matching two pictures of the same scene is a common problem in computer vision and image processing. This problem arises in connection with registering pictures obtained by different sensors, or by the same sensor at different times. In such situations, the occurrence of systematic gray level differences between the pictures, as well as geometrical distortions, often makes it impractical to use conventional correlation techniques for matching. A possible alternative is to segment the two pictures into regions, and attempt to pair off the corresponding regions based on their properties (color, size, shape, etc.) [1]; but this approach depends on the reliability of the segmentation process.

This paper explores another approach, based on extracting a set of local features from each picture, and then matching the resulting point patterns (of local feature positions). We will not discuss the nature of the local features; they might, for example, be corners on a contour or branch points on a curve. We do assume that the local feature extraction process will be relatively stable under the changes that take place from one picture to another. In any case, it will be seen that the matching process is relatively insensitive to the addition and deletion of feature points. This paper is an abridgement of a more detailed report [2], which is the first author's M.S. thesis; it also includes some supplemental results that were subsequently obtained by the third author, who acknowledges the guidance of Charles R. Dyer in carrying out this work.

In ear ier related work, Simon et al. [3] investigates the matching of point patterns by matching sets of interpoint distances; their method is applicable only to patterns that contain equal numbers of points. Zahn [4] matches point patterns by comparing their minimal spanning trees; this approach is sensitive to point additions and deletions that change the structure of the trees. Seidl [5] proposes measures of point pattern similarity based on mutual nearest neighbor relations, but does not show how useful these measures might be in practice when matching noisy or distorted patterns.

Section 2 of this paper describes the basic matching algorithm and gives examples of its use. Section 3 studies the effects of addition/deletion and random walk noise, as well as rotation and rescaling, on the matching process. Section 4 deals with the use of feature labels, associated with the points, to reduce noise effects. Section 5 discusses the results and suggests directions for further work.

2. Point pattern matching

The basic point pattern matching algorithm operates as follows: Suppose that we are given two point patterns $\Pi: P_1, \ldots, P_m$ and $\Xi: Q_1, \ldots, Q_n$, as well as a match tolerance t. We want to find a translation that maps Π onto Ξ as well as possible. Let T be the set of possible translations (we assume the translations to be quantized, so that T is a finite set). For each pair of P's (P_i, P_j) and each pair of Q's (Q_h, Q_k), we check whether the vector difference $\overline{P_i P_j} - \overline{Q_h Q_k}$ has magnitude less than t; if so, the translation that maps P_i onto Q_h (and hence, approximately, P_j onto Q_k) is a possible mapping of Π onto Ξ, and we increment the merit of this translation by 1. This process is repeated for each pair of pairs. If Π is reasonably similar to Ξ, this should result in a cluster of high merit values corresponding to translation(s) that map Π onto Ξ.

The following are some comments on the relationship between this algorithm and a correlation approach. Ordinary cross-correlation (shift, pointwise multiply, and sum) would not be very useful for matching point patterns in the presence of distortion, since most of the points will not match up exactly and so will not contribute to the sum. (This assumes that the points are 1's on a background of 0's.) However, we can introduce a tolerance into the correlation process by "blurring" one set of points into disks; when the other points, after shifting, fall on these disks, they do contribute to the sum. Our algorithm is roughly equivalent to correlating one pattern (unblurred) with a blurred version of the other pattern; the score for a given displacement is related to the number of displaced points that fall on disks. However, our algorithm may be computationally cheaper if the patterns are very sparse, since the cost of correlation goes up with the array size, whereas our algorithm depends only on the number of points.

Several examples of the use of this algorithm will now be given. Figure 1 shows a picture of an armored tank on which two people had independently selected a set of 20 or fewer significant feature points (indicated by circles); note that these sets have only about half the points in common. Figure 2 shows the array of merit values corresponding to relative translations of these two point patterns. As can be seen, there is a major peak indicating the translation for which the best match occurs. Figures 3 and 4 show similar results for a roadmap of the Washington, D.C. area. In all these examples, the point positions are coarsely quantized using a 32x32 grid.

The tolerance t used in our experiments was taken to be a specified fraction of the point pair displacements (i.e., of min $[\overline{P_iP_j}, \overline{Q_hQ_k}]$). In Figure 2, t was 10%; Figure 4a-d shows the results of using t=0, 5%, 10%, and 15%. In the subsequent experiments we used t=5%.

Figure 5 shows results for three FLIR images of a tank selected from a sequence of frames. Feature points were automatically selected by applying an edge detector, based on differences of averages taken over 4-by-4 blocks of pixels, suppressing nonmaxima, and thresholding to retain the best 30 to 35 points. Arrays of merit values are shown for comparisons of frames 1 and 5, 5 and 10, and 1 and 10. They show strong clustering corresponding to the motion of the tank from frame to frame.

Figures 6 and 7 show the results of an analogous experiment using two different feature detectors (namely, edge detectors based on differences of 2x2 averages and of 4x4 averages) for FLIR images of a tank and of an APC. Here again, strong clustering is apparent. The weaker secondary responses in Figures 5-7 represent matches between one edge of the tank (or APC) and the other; the smearing out of the responses represents matches between different parts of the same edges.

3. Noise effects

The matching process is evidently relatively immune to random addition and deletion of points, since it yields good match peaks even on patterns that have only half of their points in common. It is sensitive, however, to random displacements of the points, if these usually exceed the match tolerance. To illustrate this, Figure 8 shows the effects of applying various amounts of random jump noise to the first set of map feature points in Figure 3. The jump for each point was independently chosen, with direction uniformly distributed in $[0,2\pi]$, and with magnitude normally distributed with mean 0 and standard deviations of about 3%, $4\frac{1}{2}$%, 6%, and 9%. The corresponding arrays of merit values are shown in Figure 9; all of them display clustering, but it is much weaker for the higher noise magnitudes.

The matching process is also quite sensitive to geometrical transformations such as rotation and scale change, since it assumes that the patterns differ only by translation. Figure 10 shows merit arrays for the other set of map feature points matched against itself rotated 5° and 10°; clustering is detectable only for the 5° rotation. Figure 11 shows analogous results for rescalings of 2%, 5%, 10%, and 20%; the first three of these still show clustering.

4. Labelled point pattern matching

Up to now we have considered only patterns of identical points. This required us to use a relatively low match tolerance t=5%, since higher t's would yield many ambiguous matches. As a result, the matching process was relatively sensitive to point displacement and other distortions.

This noise sensitivity can be reduced by allowing the points to have labels (e.g., representing types of features). This permits the match tolerance to be increased without greatly increasing the ambiguity, since pairs of points having the same labels are less likely to match by chance. To illustrate this, in the road map example the points were labelled by junction types as shown in Table 1. The match tolerance was then increased to 15%. This yielded useful clustering over a wider range of noise and distortion conditions. For example, Figure 12 shows rotation results for 5° and 10°; clustering is now apparent for both angles.

5. Conclusions

The point pattern matching algorithm described in this paper is very simplistic; it only considers points pairwise, and uses a simple threshold t to decide whether or not a given pair of pairs match. Nevertheless, it seems to yield useful results in a variety of cases, and should be applicable to situations where the pictures to be matched differ primarily by a translation, and where local features can be detected with reasonable reliability in both pictures.

As a generalization of our algorithm, we could allow the merit increments to depend on the value of the discrepancy, rather than simply using a unit increment when the discrepancy is below threshold. This would be roughly equivalent to "chamfer matching" the two patterns [6]; compare the remarks in Section 2 about matching dots with disks.

The computational cost of the algorithm is relatively high, since it compares all possible pairs of point pairs. When labelled points are used, this cost is greatly reduced. For feature points that lie along borders or curves, one could also use their order as a constraint on which pairs to match; compare [7]. Further reduction should be possible by employing relaxation-like techniques [8] to eliminate possible pairings based on local evidence. Heuristic search techniques might also be used to find good overall matchings.

Other methods can be used to match point patterns that differ by transformations other than translation. As a simple example, suppose that the patterns differ by rotation about a known center. We can histogram the set of slopes defined by all the point pairs in each pattern, and then find the cyclic shift that yields the best match between the two histograms. This idea is illustrated in Figure 13.

It is well known [9] that when matching pictures that may differ substantially in grayscale, it is advantageous to match edge detector outputs for the pictures rather than the pictures themselves, since the edge outputs represent the geometry of the pictures' contents without being greatly affected by the gray level differences. The present approach, using the outputs of local feature detectors, can be regarded as a generalization of the edge-based approach.

In summary, feature point pattern matching seems to provide a potentially useful approach to picture matching under substantial grayscale modification and moderate geometrical distortion. Further studies of this approach are planned.

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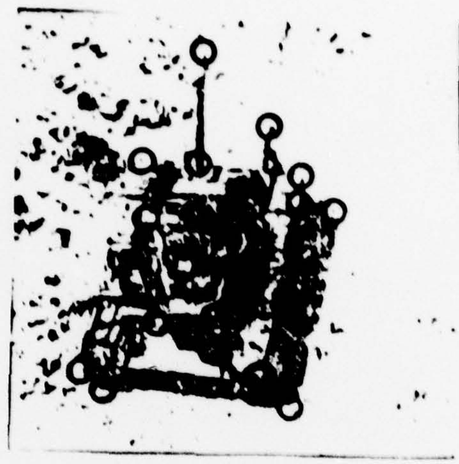
Number of Branches	Type	Label
2	Angle ("L")	0
3	"Arrow" (branches all lie in a half-plane)	1
3	"T"	2
3	"Fork" (branches not in a half-plane)	3
4	"X" (branches collinear)	4
4	Branches noncollinear	5
5 or more		6

Table 1. Junction types

Figure Captions

No.	Caption
1a-b	Two sets of feature points for tank picture
2	Array of match merit values for tank feature points
3a-b	Two sets of feature points for map
4a-d	Arrays of match merit values for tolerances of 0%, 5%, 10%, and 15% of image size
5a-c	Arrays of match merit values for edge points extracted from three infrared images of a tank: (a) Frames 1 and 5, (b) frames 5 and 10, (c) frames 1 and 10.
6a-b	a) Edge points extracted from an infrared image of a tank using two different edge detectors b) Array of match merit values for these two sets of points
7a-b	Analogous to Figure 7 for an image of an APC
8a-e	Results of applying random jump noise to the map feature points in Figure 3a. (a) Original points; (b) $\sigma = 3\%$; (c) $\sigma = 4\text{-}1/2\%$; (d) $\sigma = 6\%$; (e) $\sigma = 9\%$
9a-d	Arrays of match merit values corresponding to Figures 9b-e.
10a-b	Arrays of match merit values for the map feature points in Figure 3b under (a) 5°,and (b) 10° rotation
11a-d	Analogous to Figure 11 for rescalings of (a) 2%, (b) 5%, (c) 10%, and (d) 20%.
12a-b	Analogous to Figure 11 using labelled feature points and a tolerance of 15%.
13a-d	Numbers of slope matches as a function of rotation angle for pairs of point patterns that differ by rotations of (a) 5°, (b) 10°, (c) 15°, (d) (d) 20°.



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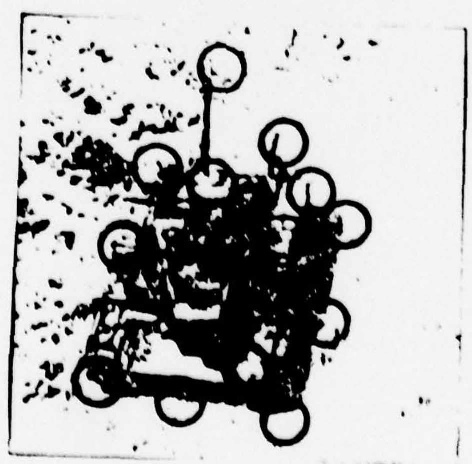

(b)

Figure 1

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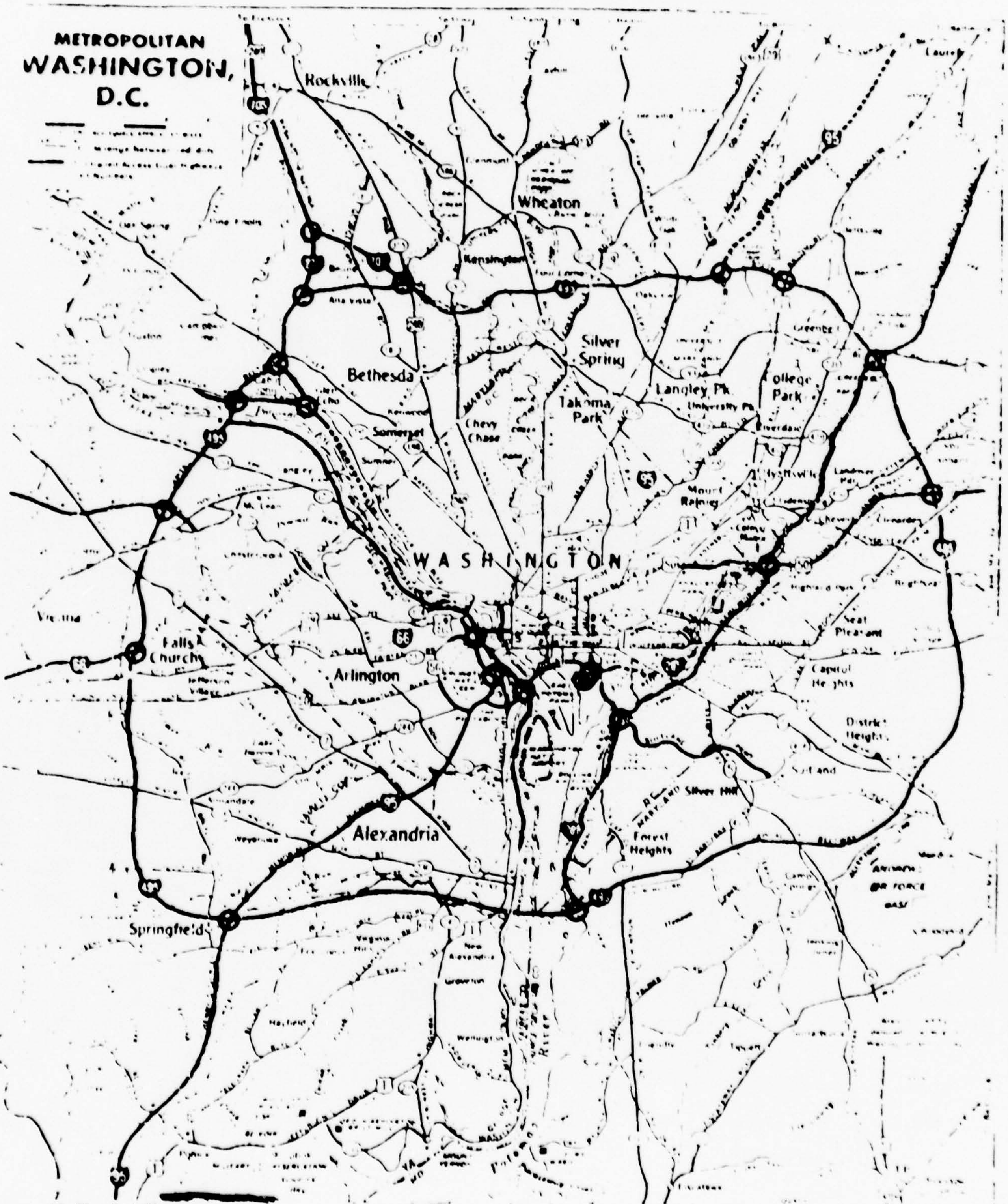

Figure 3a

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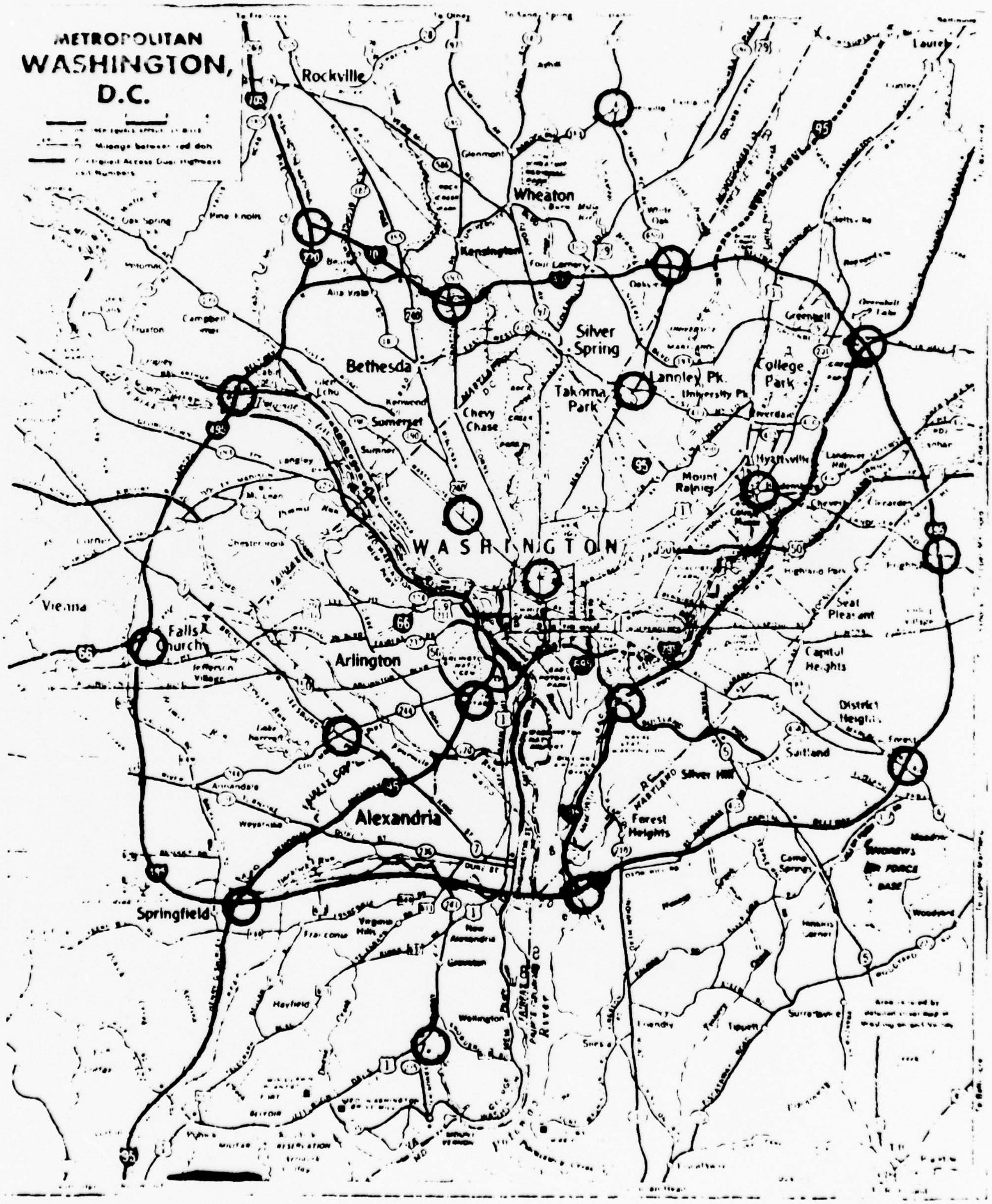


Figure 3b

Figure 4

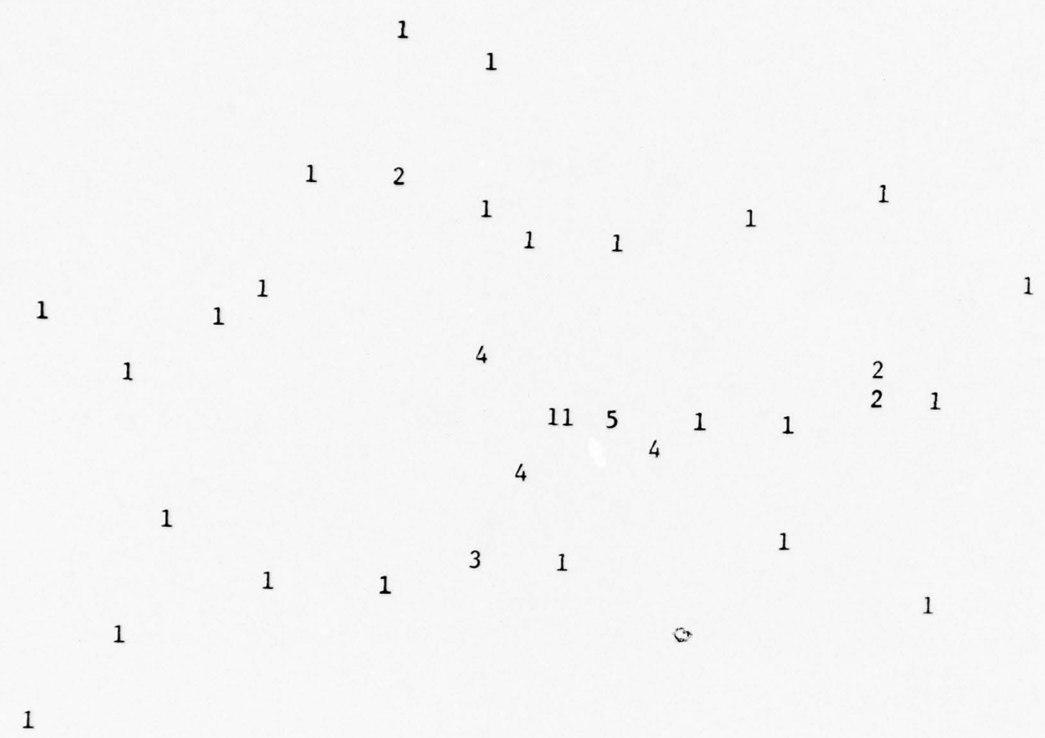


Figure 4d

							1	3	3	3	3	3	3	1			
			1	6	15	21	15	10	10	6	3	1					
	1	1	1	1													
				1	1	1					1	1	1	1	3	1	1
1	1	1	1	3	1	1		1	1								
1	1								1	3	3	3	3	1			
1		1	3	10	21	36	55	78	78	55	49	21	10	3	1		
3	1	1	1	1	1	1	1	1									
					1	1	2	1	1								
				1	1	1	2	1	1								
				1	4	6	13	10	16	15	16	10	7	3	2		

Figure 5a

```
           1  3  6 10 10 10 10  6  6  3  1

     1  1  1  1  1     1     1  1  1  1  1

           1  3 15 15 21 28 36 21 15  6  1
           1  3 10  6 10  1

     1  1  1  1                    1  1

                    1  3  6  6  3  1
              1  3  3  1
```

Figure 5b

```
           1  3  6 10 10 10 10  6  3  1
  1  3  3  3  3  1

  1  1  1  1  1              1     1  1  1  1  1

           1  6 15 21 32 36 36 21 10  3
     1  3  3  1     1

  2  2  2  2     1

                 2  3  7  6  7  3  2
```

Figure 5c

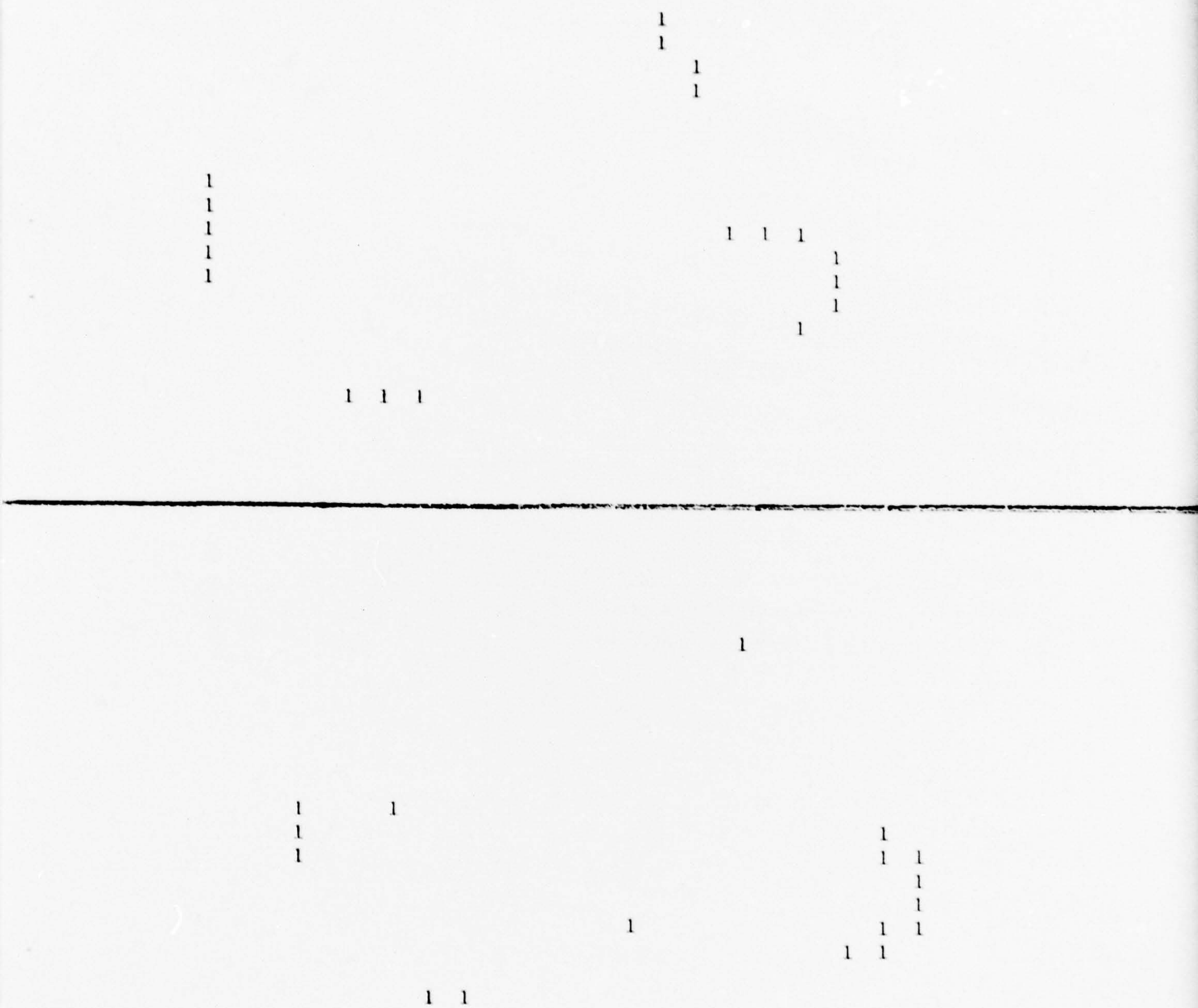


Figure 6a

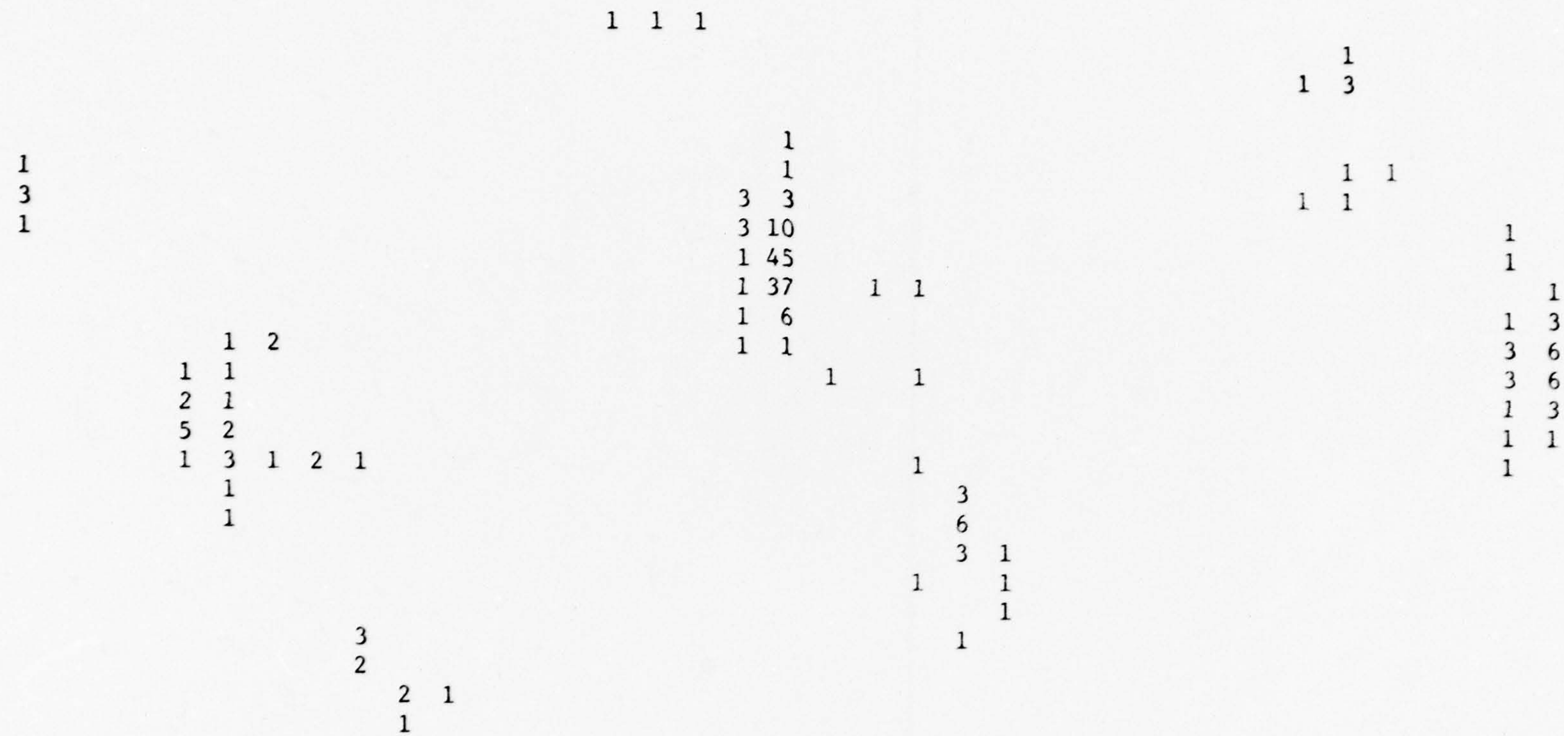


Figure 6b

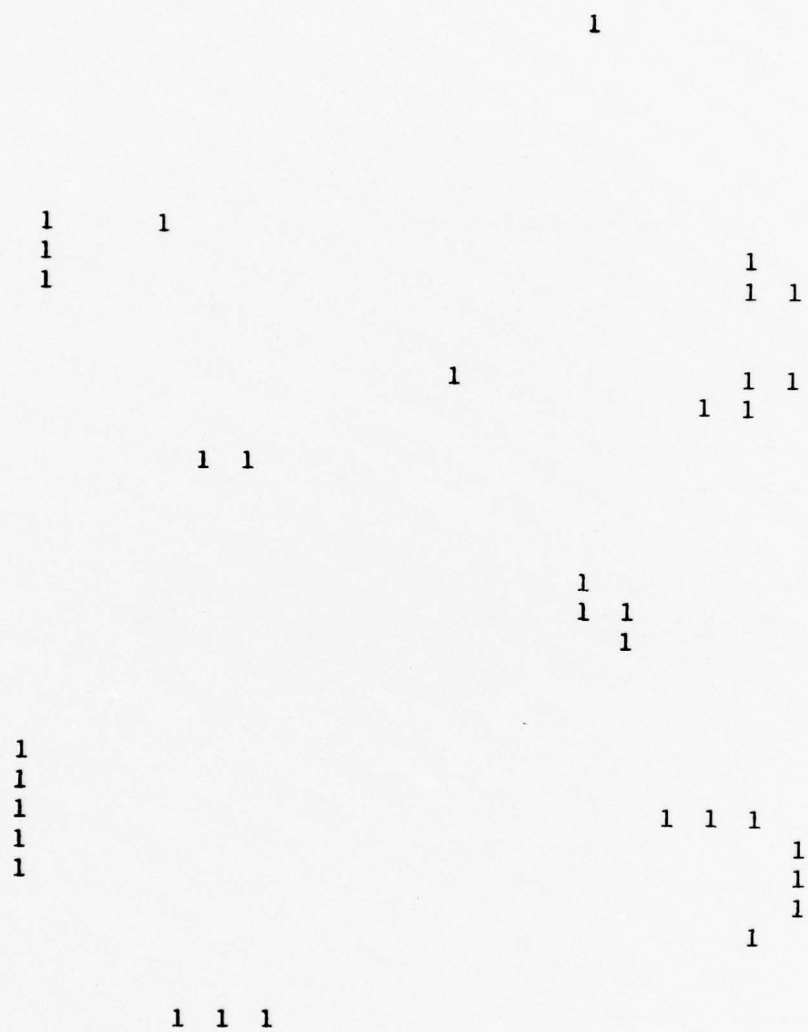
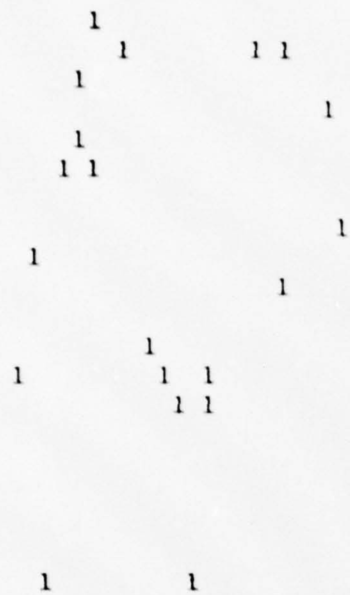


Figure 7a

								1	1				
1								1		1	1	1	
1								3		1	1	2	
1		2	1	1	3			6		1	1	3	
1		1		1	4	4	4	18	2	1	1	3	
1								21				2	
1	1		1					45	3			1	1
1			1					49	3			1	3
			6	1	1			21	1	1	2	1	4
		2	5	3	1	1	1	10	1				6
		3						6	1				5
			1					6	3				4
							1	6	3				4
													4
													2

Figure 7b



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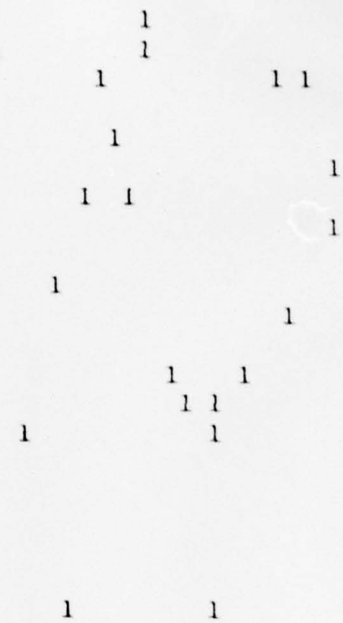

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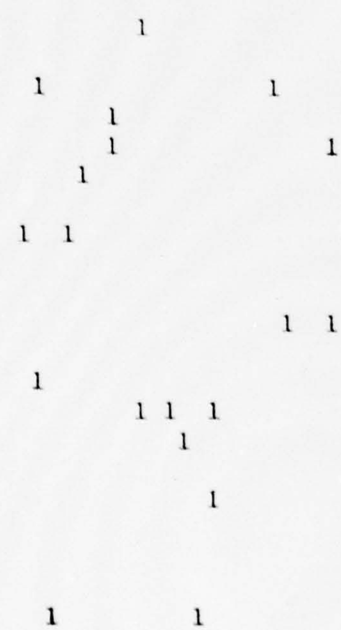
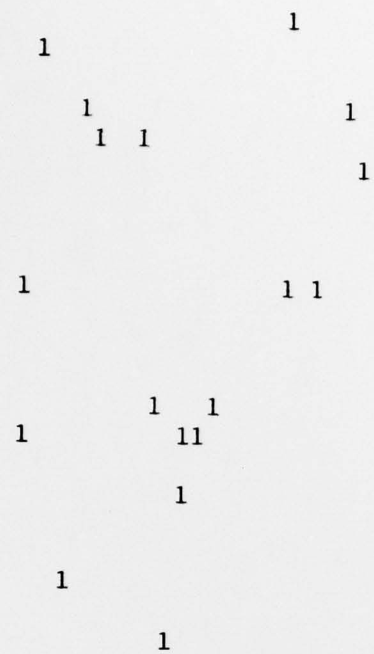


(c)

Figure 8



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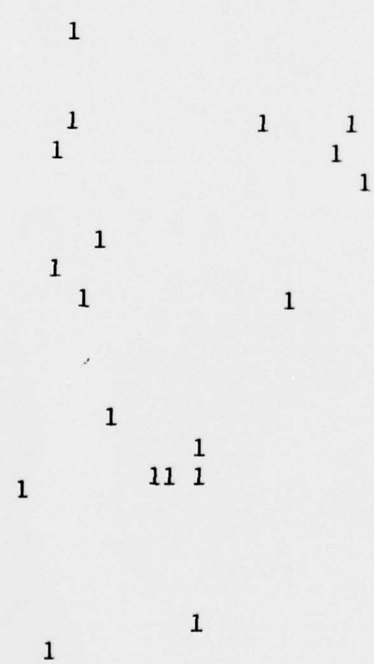

(e)

Figure 8 (continued)

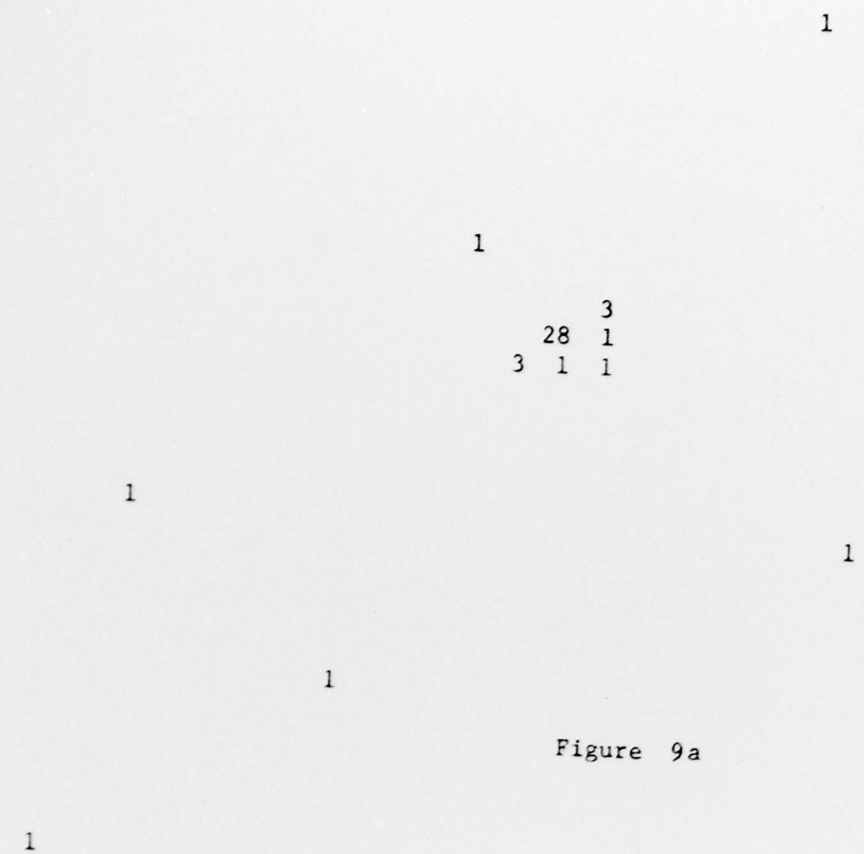

Figure 9a

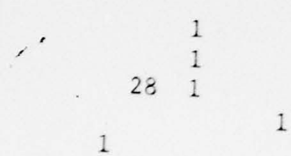

Figure 9b

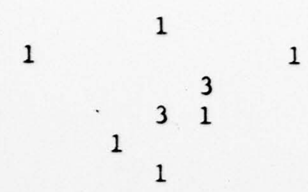

Figure 9c

Figure 9d

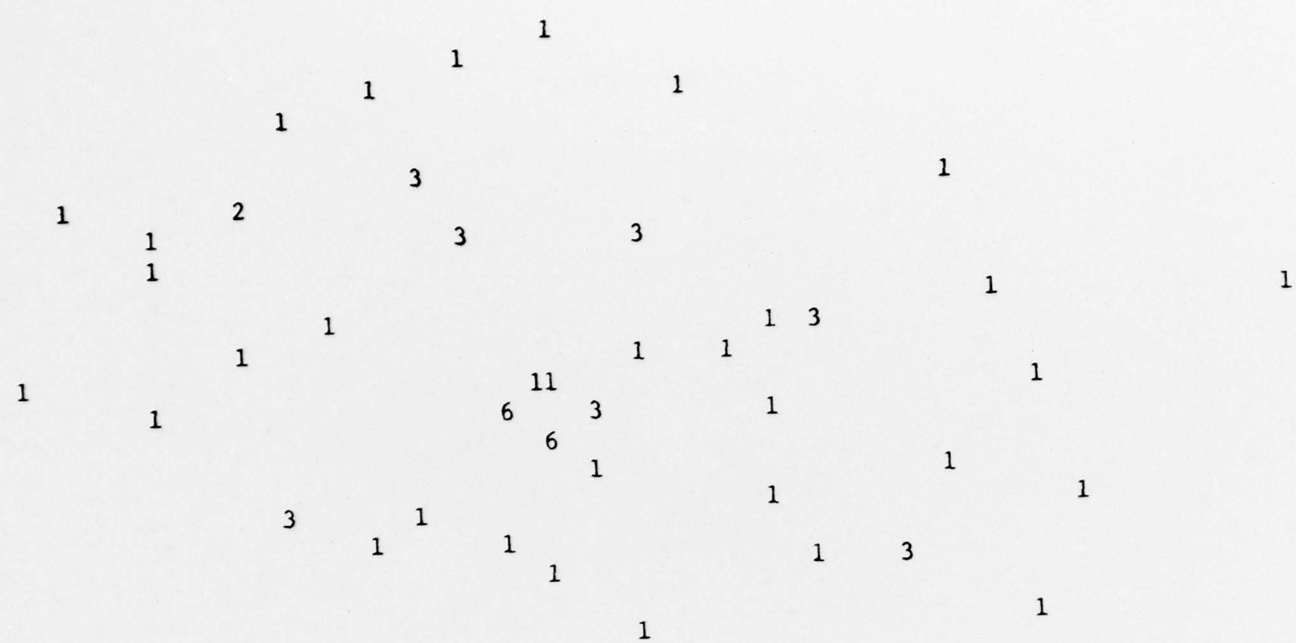

Figure 10a

Figure 10b

Figure 11a

Figure 11c

Figure 11d

Figure 12a

Figure 12b

Slope range (degrees)		Number of point pairs			
From	To	(a)	(b)	(c)	(d)
-47	-43	13	11	12	7
-42	-38	19	16	18	20
-37	-33	13	12	10	13
-32	-28	17	11	22	15
-27	-23	11	17	14	16
-22	-18	15	10	10	17
-17	-13	12	14	16	15
-12	-8	9	13	15	12
-7	-3	2	0	2	2
-2	2	42	18	11	15
3	7	<u>111</u>	32	9	10
8	12	25	<u>102</u>	44	13
13	17	16	34	<u>101</u>	29
18	22	9	7	24	<u>93</u>
23	27	10	6	12	35
28	32	17	7	7	15
33	37	15	19	16	7
38	42	12	11	9	14
43	47	10	9	10	11

Figure 13. Rotational histograms for rotations of (a) 5°, (b) 10°, (c) 15°, (d) 20°. Note that the histogram peak (underlined) in each case is in the range corresponding to the actual rotation.

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Given two pictures of a scene taken by different sensors or at different times, one way of matching the two pictures is to extract a set of distinctive local features from each, and then match the resulting point patterns. This paper investigates the sensitivity of point pattern matching to various types of noise and distortion, including omissions and additions, random walks, rotation and re-scaling, as well as the use of different feature detection operators to extract the points. The effects of additional information → next page

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(e.g., feature types) in overcoming the effects of noise is also studied.